

# **Cell-Inspired Supercomputing Chips**

- Cytomorphic & Neuromorphic Approach -

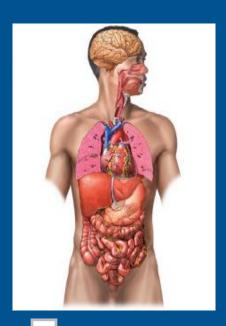
#### Jaewook Kim

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Korea Institute of Science and Technology (KIST)

25 Feb 2021

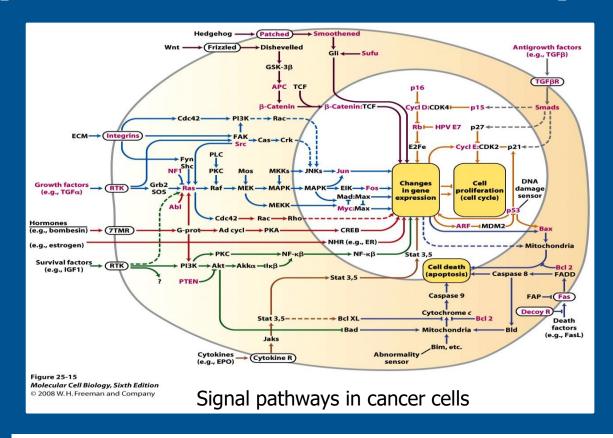
	Cellular Computation	Neural Computation	
	Animal cell  ysosome centrole centrosome peroxisome  peroxisome  centrosome  c	Cell body  Axon  Telodendria  Nucleus  Axon hillock  Synaptic terminals  Endoplasmic reticulum  Mitochondrion  Dendrite  Dendritic branches	
1. Basic computational unit device	A gene	A neuron	
2. Discrete symbolic digital output of device	An mRNA transcript	A spike	
3. Connection weighting	K <sub>d</sub> and transcription-factor binding	Synaptic weight	
4. Kinds of connections	Activatory and repressory	Excitatory and inhibitory	
5. Connections per node	~12	~6000	
6. Number of nodes	~30,000	~22 billion	
Cell-inspired supercomputing chips	Cytomorphic chip	Neurons Neuromorphic chip	

## Can we fully simulate the human body?



Disease modeling Drug testing





#### **TECHNOLOGY**

#### Skip the Humans: Drug Discovery by Simulating Cells

Virtual clinical trials would combine big data and computer simulation.

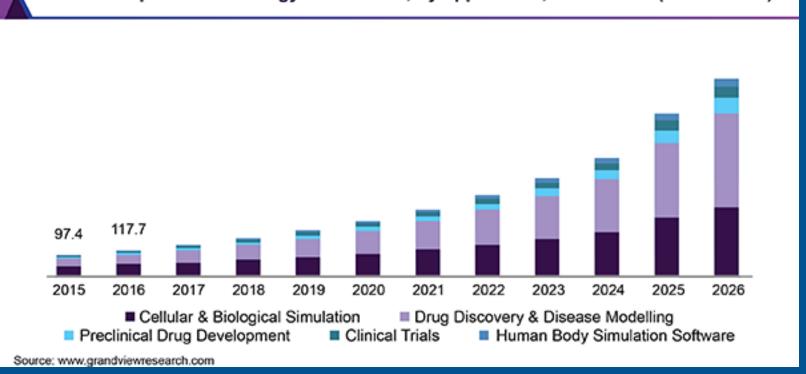
**ADRIENNE LAFRANCE** MAY 30, 2014

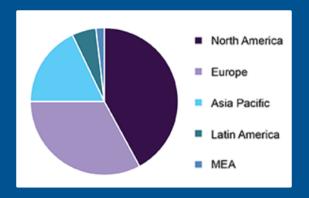
Animal testing outperformed by computer models

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## Market Size of Computational Biology

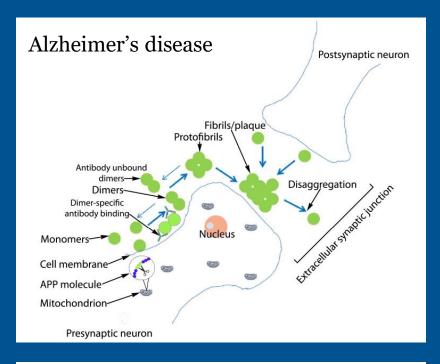
U.K. computational biology market size, by application, 2015 - 2026 (USD Million)

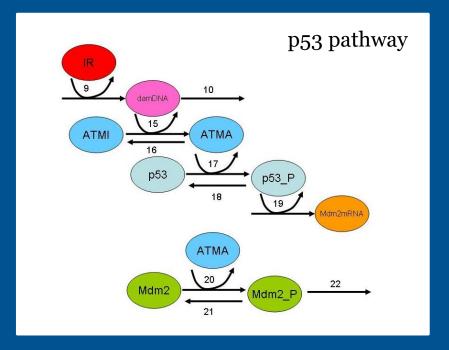


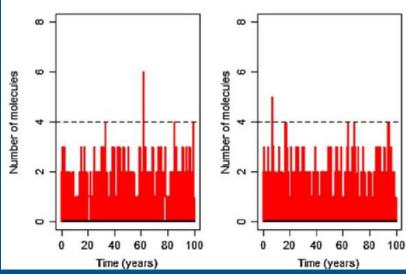


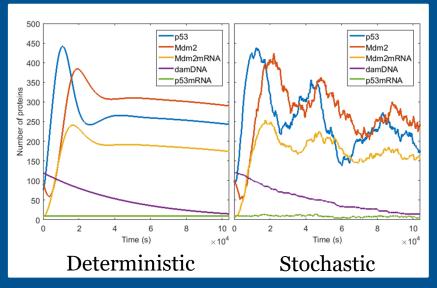
- USD 2.9 billion in 2018
- CAGR of 21.5% over the forecast period
- North America > Europe > Asia Pacific

## Importance of Stochastic Simulation

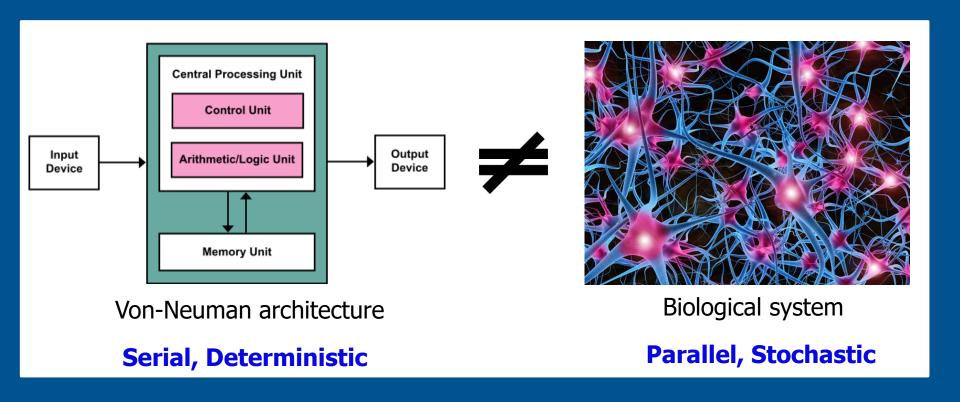








### **Problem of software simulation**

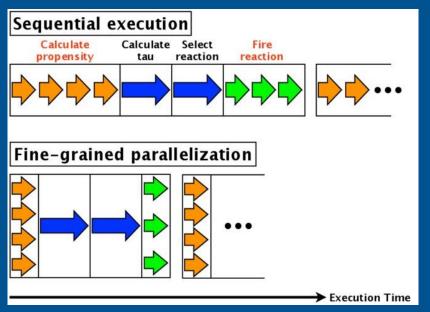


#### E. Coli simulation: 12 years

→ Long simulation time

- 10<sup>14</sup> reactions in one cell cycle
- 0.25million reactions/s
- Next reaction method (simplified model)

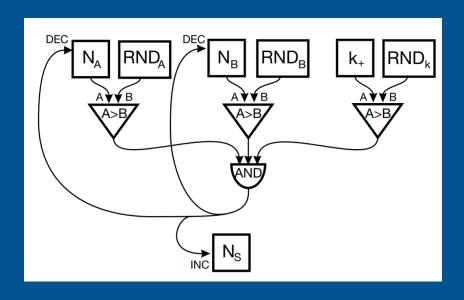
### **Previous Works: GPU**



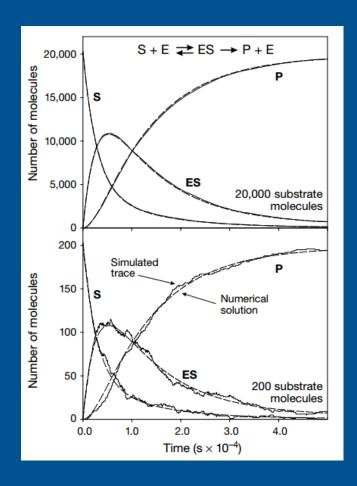
Execution time (s)		CPU/GPU
CPU	GPU	
58	0.45	128.89
70	0.59	118.64
98	0.85	115.29
142	1.54	92.21
237	2.88	82.29
406	5.52	73.55
	Execution   CPU	CPU     GPU       58     0.45       70     0.59       98     0.85       142     1.54       237     2.88

- Only certain tasks can be processed in parallel
- As model size grows, simulation time grows
- 1-2 orders of magnitude speedup for a given network

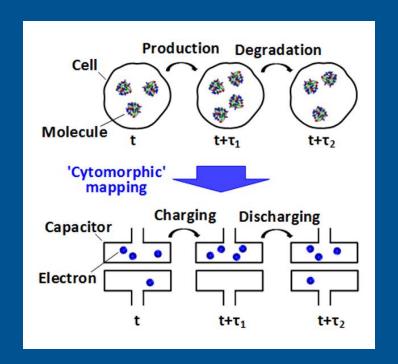
### Previous Works: Digital Hardware (FPGA)

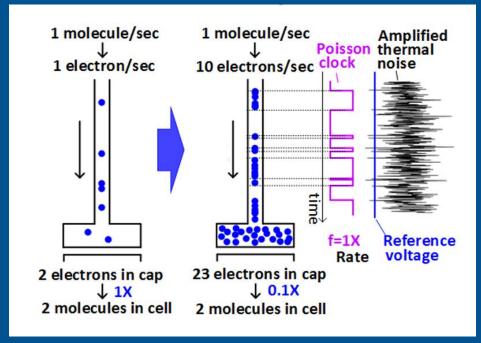


- Attempt to do parallel processing
- Discrete, same-size time steps
- An order of magnitude speedup over CPU



### The Approach of This Work





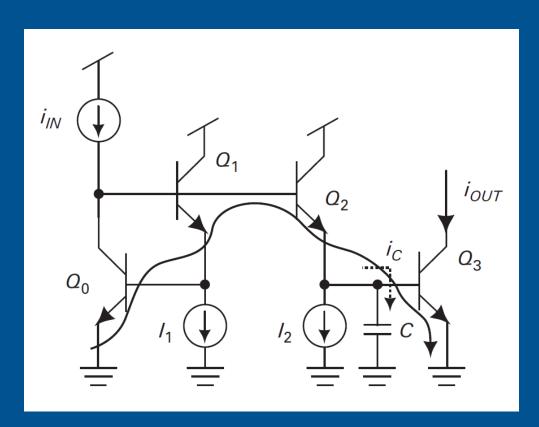
#### Cytomorphic mapping

- + Continuous-time analog building-block circuits
- + Digital circuits for programmability
- = Genuine parallel processing of stochastic biochemical simulation

### **Basis Function Circuit**

$$E + S \overset{k_f}{\underset{k_r}{\rightleftharpoons}} ES$$

$$\frac{d[ES]}{dt} = k_f[E][S] - k_r[ES]$$



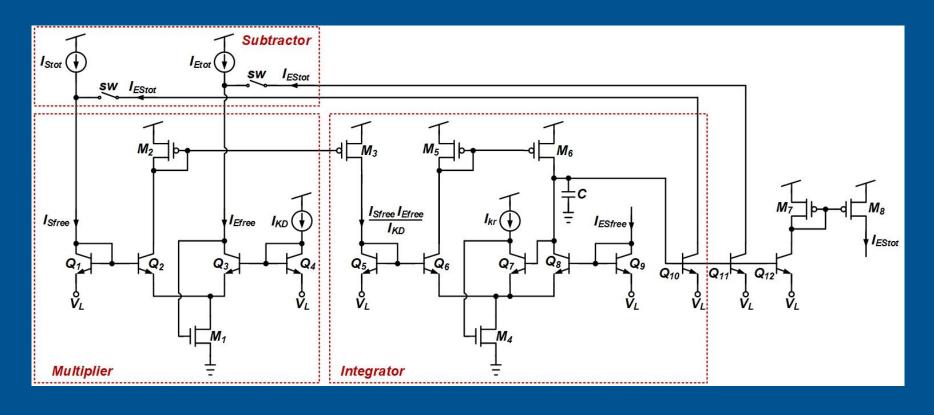
$$i_{IN}I_{1} = (I_{2} + iC)i_{OUT}$$

$$i_{C} = \frac{C\phi_{t}}{\eta} \frac{1}{i_{OUT}} \frac{di_{OUT}}{dt}$$

$$\frac{di_{OUT}}{dt} = \left(\frac{i_{IN}I_{1}}{I_{2}} - i_{OUT}\right) \cdot \frac{I_{2}\eta}{C\phi_{t}}$$

Dynamic translinear low-pass filter

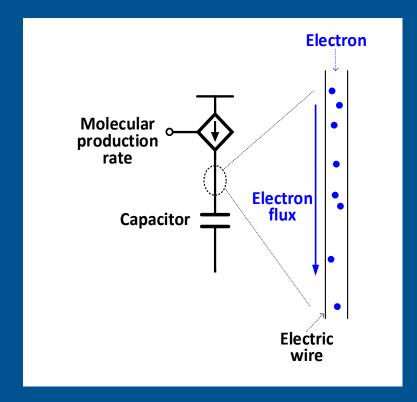
### **Basis Function Circuit**

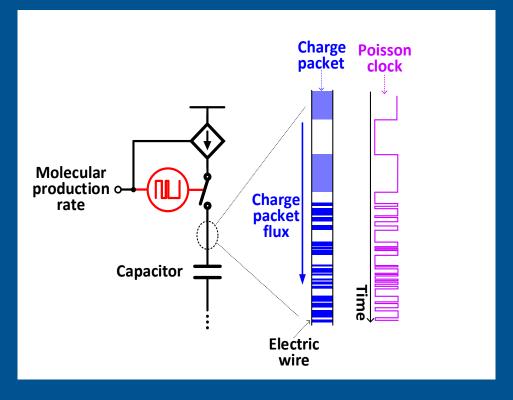


$$\frac{dI_{ES}}{dt} = \left(\frac{I_{Sfree}I_{Efree}}{I_{KD}} - I_{ESfree}\right) \cdot \frac{I_{kr}}{C\phi_t}$$

$$\frac{d[ES]}{dt} = k_f[E][S] - k_r[ES]$$

### **Stochastic Circuits**

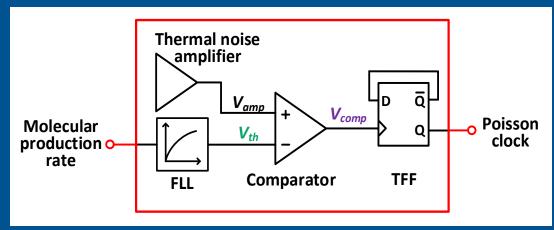




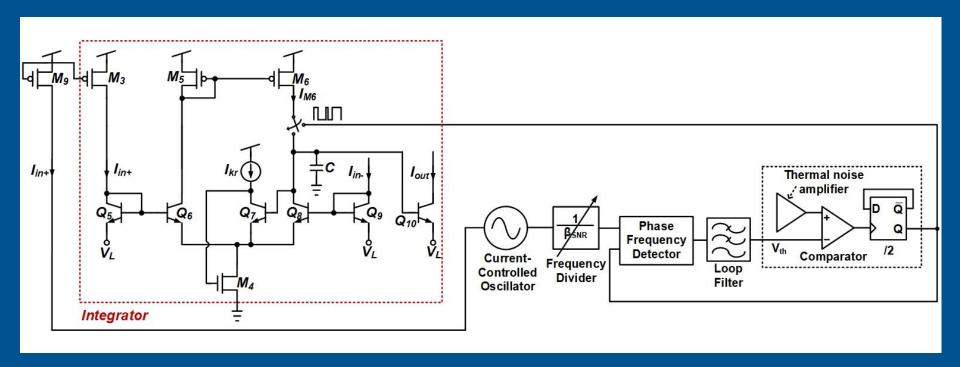
#### Non-ideal effect

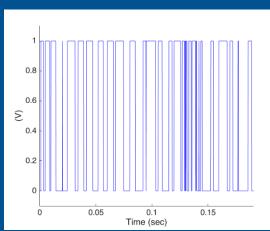
- Parasitic capacitance
- Leakage current

Difficult to emulate low # of molecules (<100)

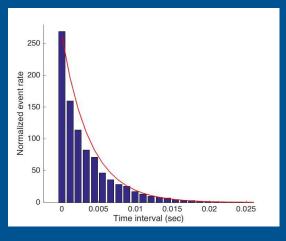


### **Stochastic Circuits**

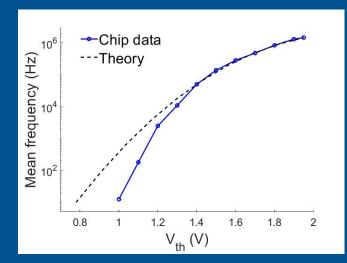




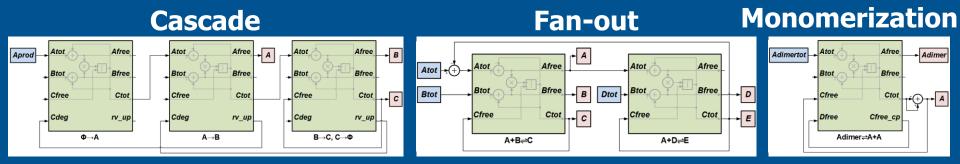
Measured waveform  $(I_{in}=10nA)$ 



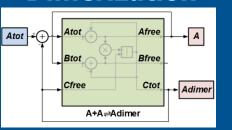
Time-interval histogram



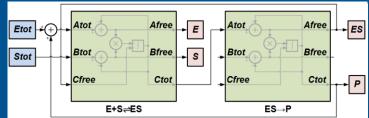
# **Any Topology Is Possible**



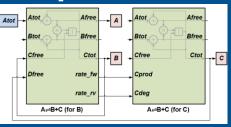
#### **Dimerization**



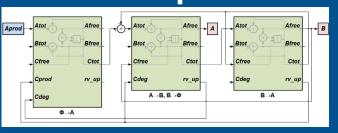
#### **Michaelis-Menten**



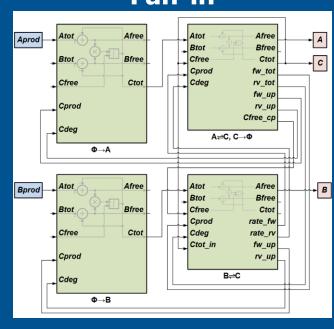
#### Replacement



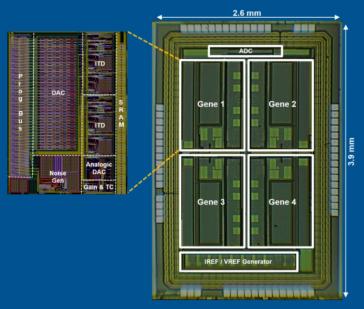
Loop

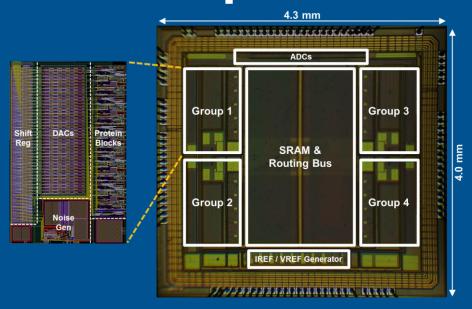


#### Fan-in



## **Gene and Protein Chips**





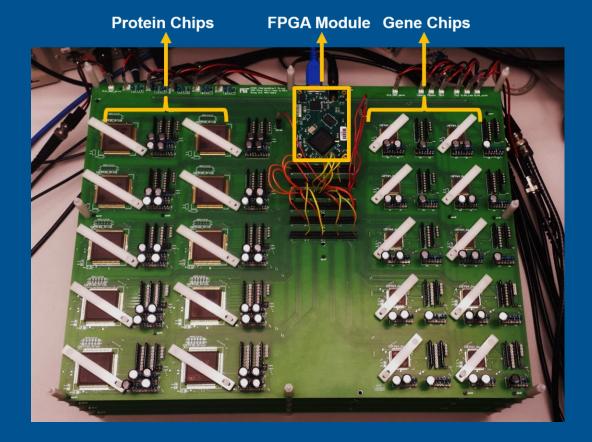
#### **The Gene Chip**

#### **The Protein Chip**

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Purpose	DNA/RNA networks	Protein/metabolite networks
Technology	AMS 0.35 µm BiCMOS	
Number of Reactions	80	60
Dynamic Range of Variables	100 dB	
Number of Noise Generators	4	
Number of ADCs	12	24
Number of DACs	160	164
Power Consumption	< 30 mW	
Programmability	Connectivity, reaction rate, initial condition, Hill coefficient	

- J. Kim, et al. "Fast and Precise Simulation of Stochastic Biochemical Reactions with Amplified Thermal Noise in Transistor Chips," IEEE TBCAS, 2018
- S. -S. Woo, et al. "A digitally programmable cytomorphic chip for simulation of arbitrary biochemical reaction networks." *IEEE TBCAS*, 2018

## **The Cytomorphic Board**







• Dimensions: 15.9 x 12.0 in<sup>2</sup>

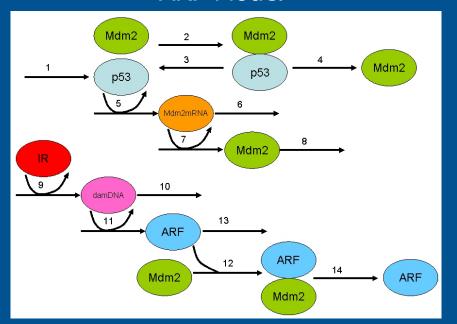
Gene Chips: 10Protein Chips: 10

FPGA Module: Opal Kelly's XEM6310 (features Xilinx Spartan-6)

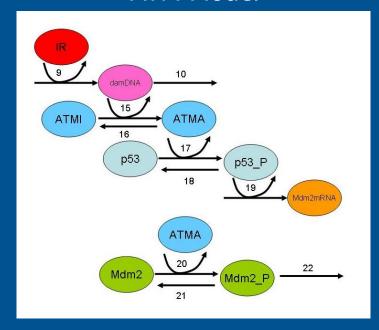
Computing Power: 1,400 Reactions

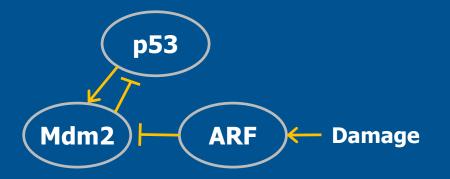
### Test Results (p53 Signaling Pathway)

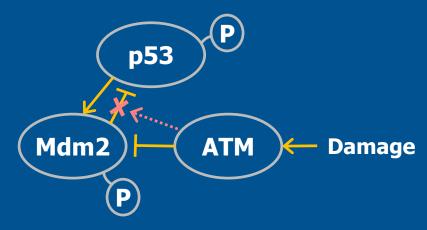
#### **ARF Model**



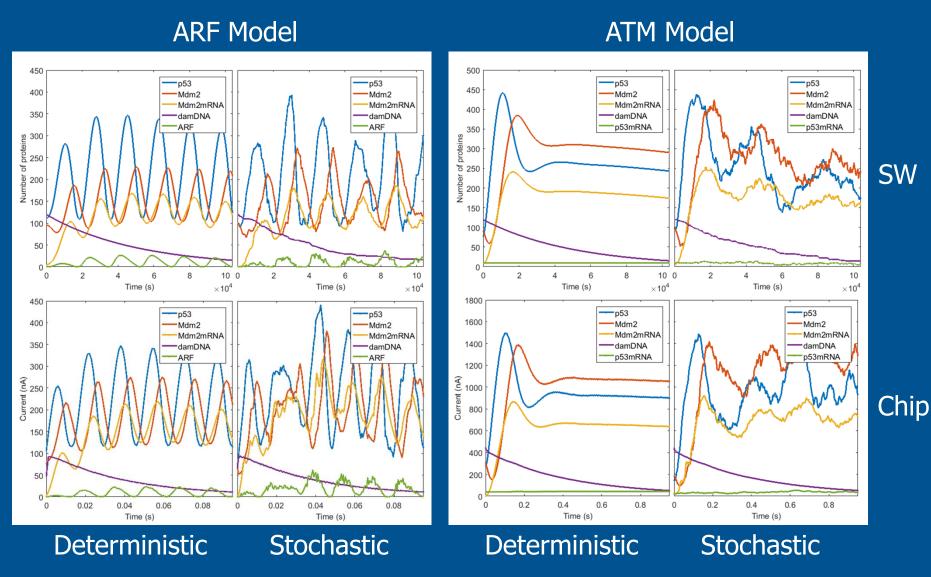
#### **ATM Model**







### Test Results (p53 Signaling Pathway)



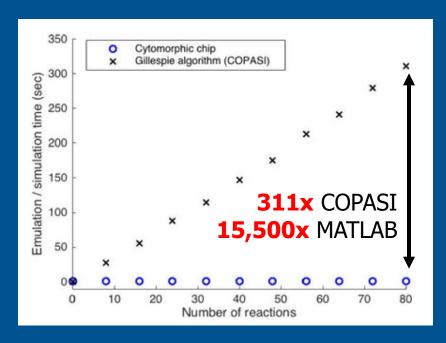
S. -S. Woo, J. Kim, and R. Sarpeshkar. "A digitally programmable cytomorphic chip for simulation of arbitrary biochemical reaction networks." *IEEE TBCAS*, 2018

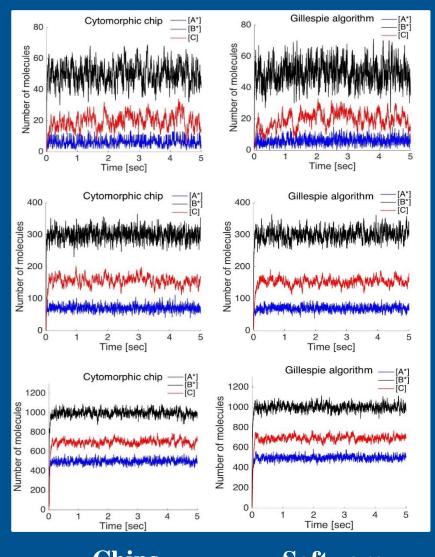
### Speed vs. Scale

$$\phi \xrightarrow{K_{prodA}} A \xrightarrow{K_{degA}[A^*]} \phi$$

$$\phi \xrightarrow{K_{prodB}} B \xrightarrow{K_{degB}[B^*]} \phi$$

$$A + B \xrightarrow{K_{assoc}[A^*][B^*]} C$$





Chips

Software

J. Kim, S.-S. Woo, and R. Sarpeshkar, "Fast and Precise Simulation of Stochastic Biochemical Reactions with Amplified Thermal Noise in Transistor Chips," *IEEE TBCAS*, 2018

## Classification of Neuromorphic Systems

Software strategies

Deep neural networks

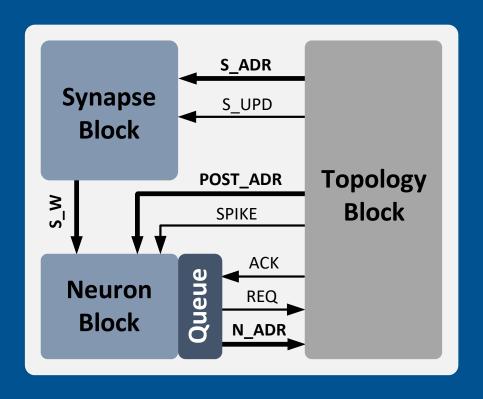
Deep learning

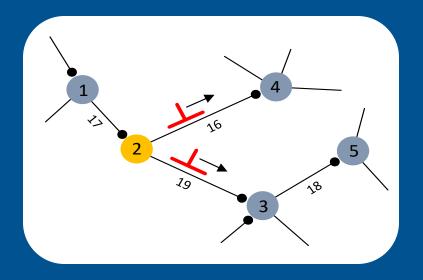


Hardware strategies				
Deep neural networks	Spiking neural networks (SNN)			
Deep learning accelerators based on GPU	Training with the aid of computers  Standalone training		aining	
	Synaptic weight storage		Synaptic weight storage	
	SRAM  IBM  TrueNorth  (2014)	Emerging memories : RRAM	SRAM  Intel KIST  Loihi Neo <sup>2</sup> C (2017) (2018)	Emerging memories : RRAM
Non-standalone neuromorphic systems		Standalone		
Offline learning only		Online learning		

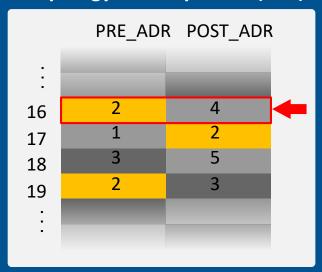
Difficulty

## **Architecture of a Neuromorphic Core**

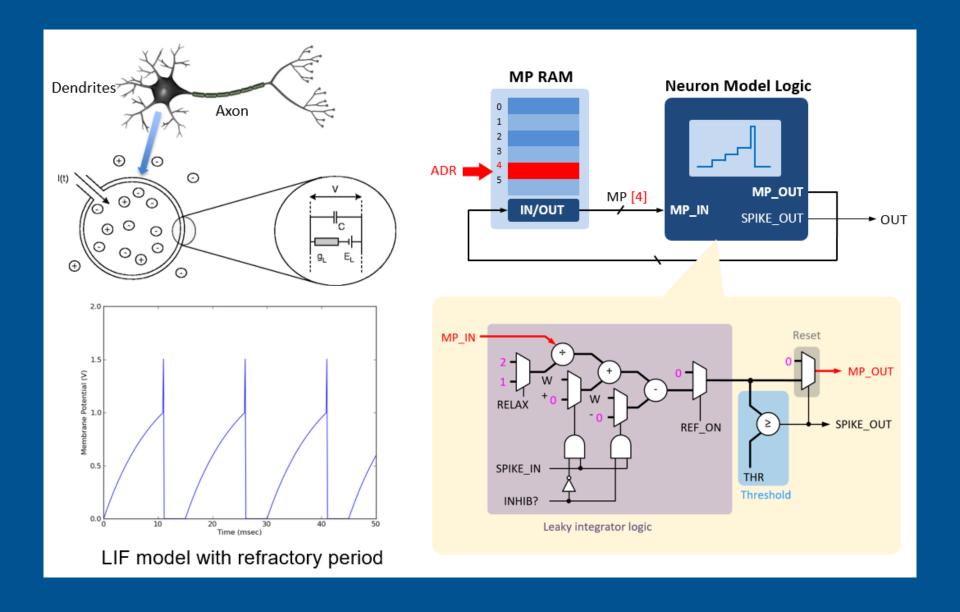




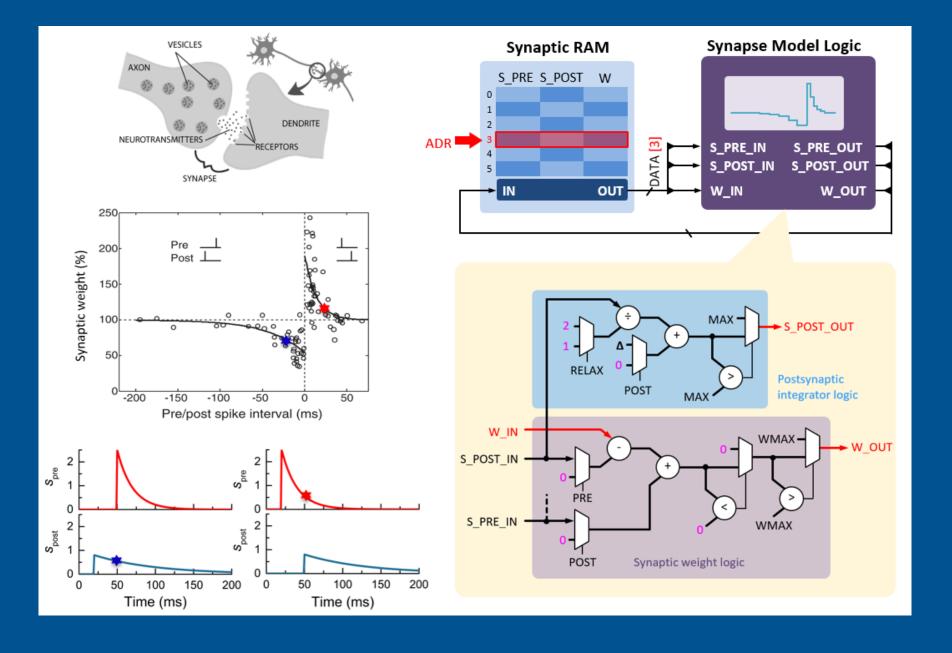
#### **Topology Look-Up Table (LUT)**



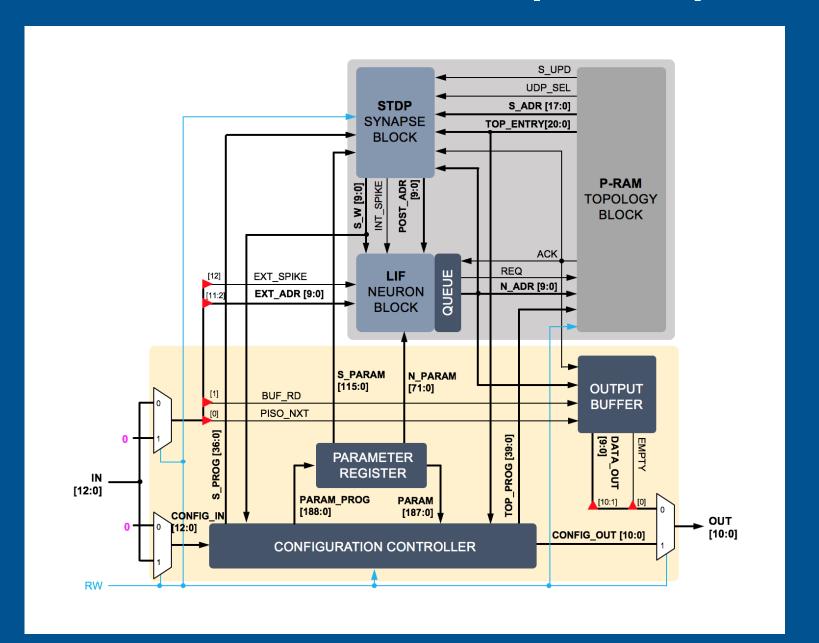
### Leaky-Integrate and Fire (LIF) Neuron



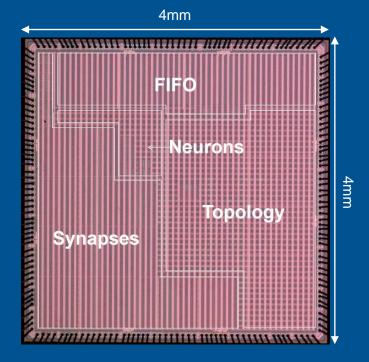
### Spike-Timing Dependent Plasticity Synapse

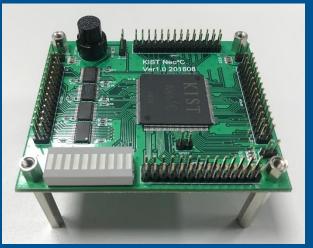


## KIST Neo<sup>2</sup>C neuromorphic chip



## KIST Neo<sup>2</sup>C neuromorphic chip

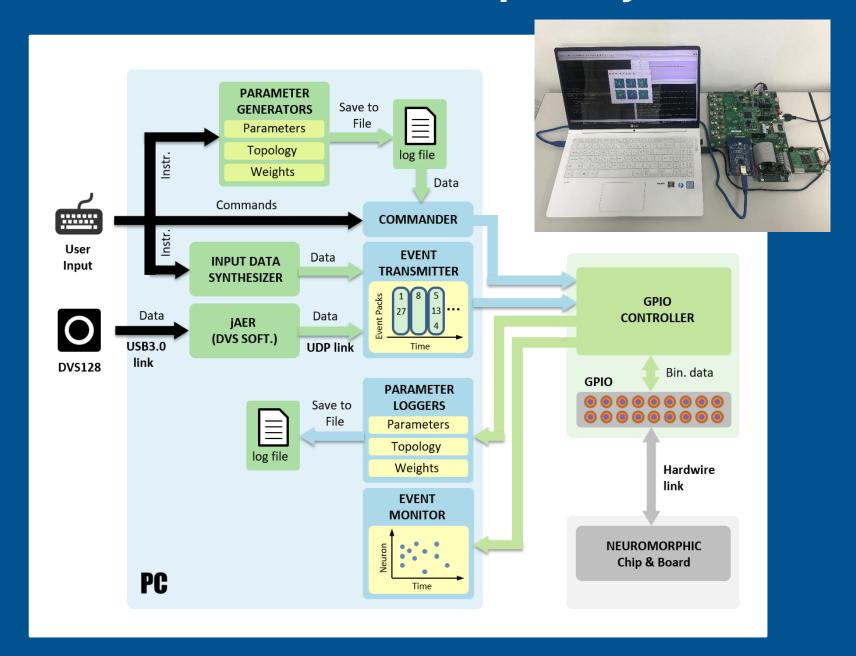


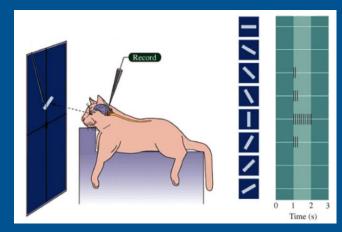


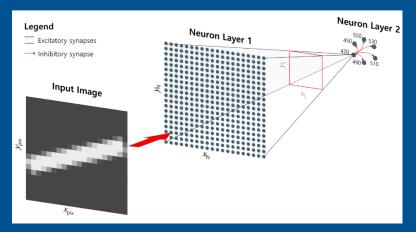
Parameters	KIST Neo <sup>2</sup> C
Process & technology	55 nm CMOS
Area	16 mm²
Number of neurons	1,024
Number of synapses	199,680
Number of cores	1
On-chip learning	Yes
Learning rule	STDP
Supply voltage	1 V
Clock frequency	100 MHz
Power consumption	56 mW

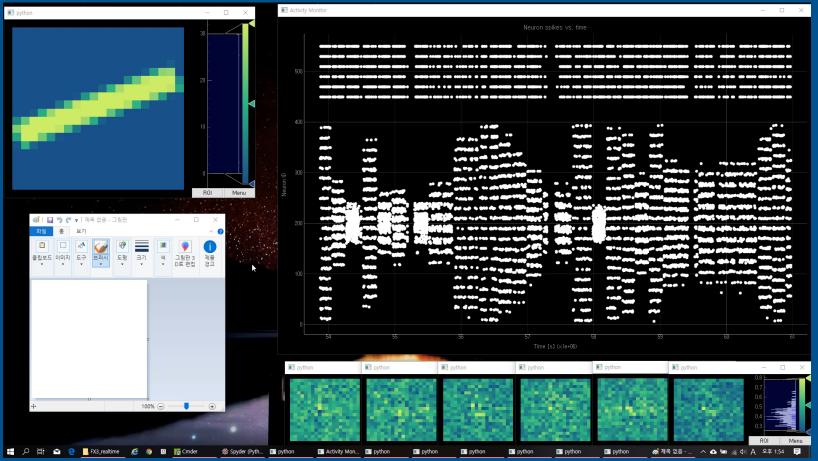
- Fully reconfigurable spiking neuromorphic system
- On-chip, online, unsupervised learning
- Learning rule: STDP with all-to-all spike interaction
- Fully digital implementation

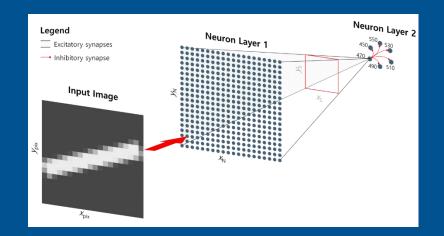
### KIST Neo<sup>2</sup>C neuromorphic system

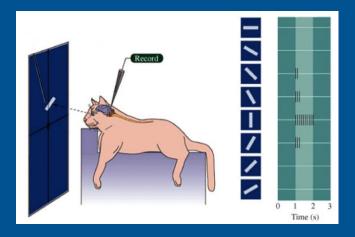


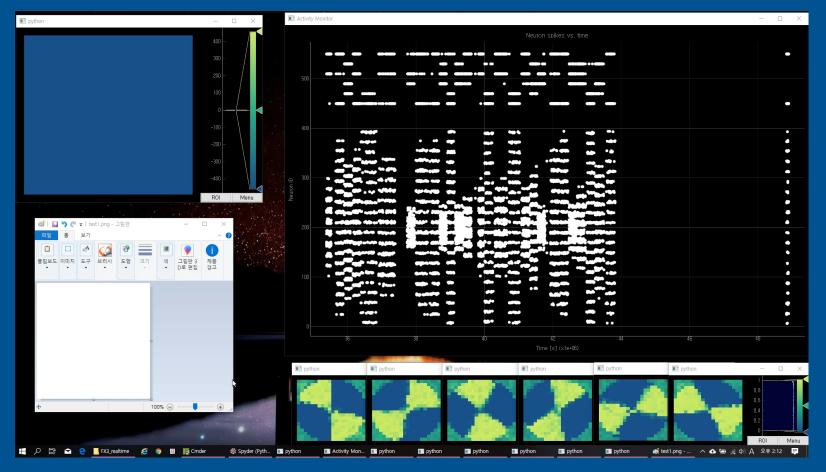












# Acknowledgements

### Cytomorphic chip project

- Dr. Sungsik Woo
- Prof. Rahul Sarpeshkar





### **Neuromorphic chip project**

- Dr. Vladimir Kornijcuk
- Prof. Dooseok Jeong
- Dr. Joonyoung Kwak
- Dr. Jongkil Park
- Dr. Joonyeon Chang





# Thank you for your attention!